Business Models for Distributed Power Generation

The case of microgrids

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Abstract

There is widespread interest in possible transformations to the electric power industry toward a more decentralized system of supply and response, and microgrids could be central to that transformation. In addition to improving power quality, reliability and resiliency, microgrids are also often cited as a means to provide macro grid services and integrate favored generation sources such as renewables. The actual use of microgrids, however, hinges on the "business model" through which real investors might deploy microgrid systems. We offer a tool for assessing business models based on the widely used Distributed Energy Resources Customer Adoption Model (DER-CAM) modeling framework and present three main findings. First, the microgrid literature is somewhat scattered in its insights partly because microgrids exist in many forms—they employ many different suites of technologies and operate under various business models. As such, we offer three "iconic" types of microgrids which align with forecasted market growth—commercial buildings, critical assets such as hospitals for which reliability is paramount, and large campus-sized systems—and report typical electric and thermal loads by month and type of day for each. Second, we find that optimal configurations for each of these three iconic microgrids leads to some deployment of renewables, but the main financial value in microgrid business investments is rooted in the potential to utilize natural gas. This finding contrasts sharply with most policy advocacy, which has focused on deployment of renewables and energy storage. Third, we find that business models are robust across uncertainty in numerous parameters. We identify those parameters that most affect business models—the price of natural gas, cost of carbon, electric tariff costs, and the cost of energy storage—and quantify their impact on investment cases and subsequent business models. We show that costs charged by the local utility and special incentives for preferred generation technologies such as renewables are likely to be the most important areas for microgrid policy intervention.

Contents

1. Introduction

The electric industry is undergoing a transformation on many fronts—most strikingly, perhaps, in the character of the distribution system. Many non-traditional entities are now influencing local balance of power supply and demand, thereby decentralizing power generation. Technology has been a primary driver—the economics of distributed energy resource (DER) technologies have improved radically, such as through innovation in solar photovoltaic (PV) systems, smart metering, energy storage, fuel cells, microturbines, electric vehicles (EVs) and controllers that enable demand response and energy efficiency measures.

In many jurisdictions, policy makers have enacted a host of energy regulatory policies and financial incentives that promote the growth and deployment of these technologies and that encourage participation in energy management by parties other than traditional utilities. This role for policy has been particularly profound in areas where policy makers have coupled themes of grid decentralization with decarbonization (that is, the shift to a low-carbon energy economy by transitioning from fossil fuel power generation to renewable sources), where the need for higher grid reliability and resiliency has become acute, or both.

The push for decarbonization stems from climate change and the need to stop global temperature rise—the current goal is to limit that increase to two degrees Celsius of pre-industrial levels. That push has come on several fronts, one of which is emission reduction targets, both at the federal- and state-level. In the United States (US), the 2015 federal Clean Power Plan requires individual states to reduce carbon emissions from power plants. At the state-level, 20 states have set greenhouse (GHG) emissions targets as of 2015 [1]. California, for example, passed legislation (Assembly Bill 32) to reduce GHG emissions to 1990 levels by 2020 and aims to do so in almost all economy sectors [2]. This legislation is connected to research on DERs and low-carbon microgrids (that is, microgrids that integrate high penetrations of renewables) as potential pathways to reach the reduction targets [3], [4].

Another front is utility-scale renewable power. As of 2013, 29 states have enacted a Renewable Portfolio Standard (RPS) or similar policy. These standards require energy suppliers, such as utilities, to procure and deliver a minimum fraction of energy from renewables. California, for example, recently increased its RPS from a 33 percent-by-2020 mandate to 50 percent-by-2030 [5], [6]. As with Germany's *Energiewende*, policies aimed at promoting renewable energy sources more generally such as RPSs are driving growth of some of the same technologies that could make microgrids more viable economically [7]—such as energy efficiency, battery storage, and small-scale solar PV [8]. In California, RPS mandates are linked to new requirements for energy storage deployment that will further decentralize the electric grid [9].

The push for renewables is present at the distribution level as well. Numerous electric tariffs promote deployment of distributed generation (DG) technologies directly—for example through Net Energy Metering (NEM) and Feed-In Tariff (FIT) programs. NEM credits (at retail electricity rates) customers with preferred technologies for excess generation. FIT programs allow customers with DG to sell power to the local utility. Some utilities are actively promoting experimental and new tariffs that could lead to the same outcome [10]. That push includes thermal energy sources and combined heat and power (CHP) systems as well. For instance, the New York State Energy Research and Development Authority (NYSERDA) recently issued $100 million in incentives to CHP units that improve grid reliability [11]. This logic helps explain why densely settled urban regions [12], [13] as well as areas with high thermal loads [14], [15] have long had elements of microgrids in operation. Indeed, the strongest business models for microgrids may lie with systems that are large enough to integrate electric and thermal loads efficiently—a finding that the present study will confirm. Within district heating systems and policies, debates about scale, integration and ownership have unfolded in ways that are quite similar to the debates on microgrids [16]. In the United Kingdom, a special tariff aims to boost the use of decentralized, renewable heating sources—notably heat pumps [17].

Some policies target decentralization directly. In California, several groups are offering visions for a more decentralized power grid in which users actively participate in the wholesale market [18], [19]. New York has adopted aggressive targets along with its Reforming the Energy Vision (REV) that will actively decentralize the power grid. Indeed, many governments in the northeastern US are focused on supposed advantages of a decentralized grid that might be more resilient [20]–[22]—a need underscored by recent severe weather that caused billions in damage and widespread blackouts. The New York University microgrid, for instance, remained electrified and heated post-Hurricane Sandy [23]. In Europe, policy schemes support virtual power plants [24]. The More Microgrids project, supported by the European Commission, found that microgrids can be profitable under current market conditions in the European Union, but suggests a new regulatory framework for local energy trading that unlocks greater economic benefits of an electric grid with microgrids [25]. In Japan, microgrid deployment became an industry focus in the wake of the Fukushima earthquake and tsunami, which caused outages to most of eastern Japan [26]. Indeed, Japan's recent Strategic Energy Plan [27] promotes distributed energy networks in favor of its historic use of large central generating stations.

Together, these three trends—new power management practices, technological innovation, and policy—radically improve the economics of microgrids as tools that integrate DERs [28]–[32], thereby potentially opening new markets for grid-connected microgrids. Actual investment has followed this potential—microgrid installations are expanding rapidly and investment is slated to accelerate further in the coming decade [33]. As these patterns spread, the result could affect how grid operators and utilities manage the electric grid and plan infrastructure development.

We focus on microgrids because they are tools that employ DERs to achieve flexibilities (namely the control of load and generation) that stand-alone DER technologies cannot—flexibilities which allow the microgrid to provide a host of benefits to adopters and to the macro grid alike. They are thus emblematic of the current transformation to the electric industry. Whereas much of the discussion around grid decentralization has been hypothetical, the rise of microgrids is a real phenomenon—making this suite of technologies particularly amenable to quantitative modeling tuned with data from real microgrid systems and forecasted market growth. We adopt the definition of the US Department of Energy (DOE), which defines a microgrid as "a group of interconnected loads and distributed energy resources within clearly defined electrical boundaries that acts as a single controllable entity with respect to the grid and that connects and disconnects from such grid to enable it to operate in both grid-connected or 'island' mode."

Though the emergence of microgrids is real and monitored closely, due to their novelty and high development cost microgrids have been implemented primarily where customers have a premium need for reliability and have not been particularly sensitive to rates—for example military bases and hospitals [34]–[36], where they can be linked to research enterprises such as university campuses [37], [38], and for remote loads that are too costly to serve by extending the macro grid [39], [40]. These conditions may be changing rapidly, however, driven by cost reductions in decentralized renewable energy technologies, rapidly improving economics of scale for batteries, and notably a favorable natural gas price [41].

As microgrids become viable economically, their development will hinge on the incentives for private investment. Microgrids must have financial returns that investors can appropriate. Here we offer a framework for how those "business models" can be assessed. The standard business model for microgrids rests on the ability to generate electricity, heating, and cooling services locally for a total cost less than utility service. Following standard practice, we look at those total costs—the annual operating costs plus the amortized expense of the required capital deployment—for the first full year of microgrid operation.

In section 2 we review the large and sprawling literature related to microgrids, focusing on modeling tools. In section 3 we configure one of those tools, DER-CAM, to make it suited to the task of evaluating microgrid investment strategies and business models. We also re-calibrate that model with recent, real-world data on performance of key technologies and market conditions such as the price of natural gas and cost of emitting carbon dioxide (CO_2). In that section we also present profiles for three typical microgrid configurations. The central contributions of this paper lie in the calibration of DER-CAM and the presentation of these three iconic microgrids that can help to standardize research in this field. In section 4 we present results that we discuss in section 5.

2. Review of the Literature

The literature on microgrids is diverse and fits broadly into two categories. The first comprises the coherent and growing literature that presents models of the techno-economic performance of microgrid systems. We see this literature as the core of the field and crucial to business model analysis. Second is a more sprawling set of studies directly and indirectly related to microgrids—on pivotal technologies (e.g., storage) and policies (e.g., regulation) along with many case studies. We examine each in turn.

2.1. Review of modeling tools

Microgrid modeling comprises several phases and is approached generally with two types of analysis: techno-economic analysis and power system analysis. Here we focus on the former because it is central to understanding business models. We note that other studies have reviewed the highly technical literature on physical power system design and network operations, and that numerous models have been developed to perform this analysis [42]–[46] (see also [47], which reviews several of these and power system analysis generally).

Techno-economic models are designed to identify the optimal economic configuration of a microgrid. Doing that requires a technical component that allows for assessment of individual elements of the microgrid—such as gas turbines, reciprocating engines, fuel cells, CHP, solar PV, energy storage, and others—in an integrated system. They also have an economic component that optimizes energy transactions between the microgrid and macro grid to meet a specified objective, such as minimizing cost. These components have been formulated into numerous techno-economic models using a variety of optimization techniques [48].

In the published, academic literature two techno-economic models dominate: the Hybrid Optimization Model for Multiple Energy Resources (HOMER) [49] and DER-CAM [50]. Several publications review these tools systematically, for example [51] and [52]. Here we review both and then briefly look to other modeling literature and tools—including proprietary tools that are not extensively used by academics because the code is not publicly replicable and such tools are expensive to operate.

2.1.1. HOMER

HOMER was developed initially by the US National Renewable Energy Laboratory (NREL), and development continues by HOMER Energy LLC. HOMER is used to determine the most cost-effective combination and capacity of technologies to meet electrical and thermal loads. Users run many simulations of specified configurations to identify the lowest lifecycle cost of the system and to study system sensitivities. HOMER can simulate grid-connected and off-grid systems; analyses of the latter are prevalent in literature. The system is technically accessible to new users and available to demo freely. That helps to explain the large size (perhaps 100,000 users) of the HOMER community.

HOMER's use in literature is dominated by case studies—often of isolated (that is, off-grid) energy systems. These case studies examine several areas of microgrid implementation: for instance, the benefit of stand-alone hybrid energy systems for rural electrification [53]–[57]; the benefit of replacing conventional generation or grid-supplied electricity with renewable energy resources [58], [59]; comparison of renewable and fossil fuel-based microgrids [60], [61]; the benefit of installing a microgrid to forego grid consumption [62]; and evaluation of break-even thresholds for business cases [63]. These case studies typically present as central results the optimal microgrid configuration and operation, and compare the net present value of the microgrid relative to grid-supplied electricity or the cost of extending the macro grid to supply the rural community.

2.1.2. DER-CAM

DER-CAM is an investment and planning tool for DER adoption in microgrids. It is used to design and simulate microgrids. The Grid Integration Group at the Lawrence Berkeley National Laboratory (LBNL) has developed DER-CAM since 2000 and development is ongoing.

DER-CAM is a mixed integer linear program written in the General Algebraic Modeling Software (GAMS) language [64], a modeling system for optimization problems. The model's objective function determines the lowest-cost combination of available DERs to supply the electricity, heating, cooling, and natural gas loads of a utility customer. Upon investment, the microgrid meets end-use consumption with energy purchases, on-site generation, or energy recovered on-site. DER-CAM first finds the optimal suite of distributed energy technologies that minimizes the total energy bill or emissions or combination thereof, and second determines the optimal operating schedule over the entire year so as to meet that objective. The model provides comprehensive accounting of investment costs in conventional, combined heat and power, and renewable technologies; energy transactions between the microgrid and macro grid; fuel consumption; and carbon emissions. Simulations capture one year and therefore also seasonal variation. The mathematical formulation of DER-CAM is presented in [65] and [66].

Key inputs to the model include utility tariff data, available DERs, and end-use loads. Outputs include the cost-minimizing combination and operation of distributed resources. Inputs are listed comprehensively in [67] and also included in the supplemental information.

DER-CAM is technology neutral and thus can be adapted to a wide array of microgrid settings—making it unwieldy to configure but particularly useful in studies such as the present one where many parameters need adjustment to real world conditions. The model considers the technical specifications and costs of several distributed technologies: (i) a suite of conventional generators such as micro turbines, gas turbines, and reciprocating engines of various capacities—with and without thermal recovery, and fueled with natural gas, diesel, or biodiesel; (ii) thermal units such as direct-fired chillers, absorption chillers, solar thermal heating, heat pumps, and thermal storage; (iii) renewable technologies such as solar PV; and (iv) emerging technologies such as fuel cells, electric energy storage and EVs. The model considers load-based capabilities as well, such as demand response and load scheduling.

DER-CAM exists in two primary branches: an investment and planning branch and an operations branch. The former determines the optimal suite and operation of distributed resources over one year, and the latter the optimal week-ahead scheduling for installed energy resources [68]. The investment and planning branch is most useful for analyzing business cases and is where we focus our attention.

Initial development of DER-CAM is documented in [69], [70]. Later developments by LBNL have, notably, included enhancements to allow analysis of particular case studies and scenarios. They include, for example, the addition of a carbon tax and its effect on microgrid CHP adoption [65], heat recovery [67], electric and thermal storage [71], power quality and reliability considerations [66], minimization of CO_2 emissions as a cost function objective [72], zero-net-energy building constraints [73], EVs [74], and building retrofits [75]. Others using DER-CAM have also systematically analyzed parameters in DER-CAM that affect microgrid economics, for example tariff structures [76], energy storage [74], and climate zones [77]. More recently, the modeling tool has been adapted to study the economic impact of EV integration in microgrids [78], the business case for ancillary service provision using electric storage in microgrids [79], and the economics of reactive power provision [80].

For our purposes, the adaptability along with extensive published record and open-source nature of the code are attractive features of the DER-CAM platform for academic research.

2.1.3. Other software tools

In addition to HOMER and DER-CAM, other modeling frameworks also allow for techno-economic assessment. RETScreen is a software package used to analyze the economics of renewable energy technologies and energy projects [81]. Though it boasts a large user base it is not particularly suited to the demands of microgrid analysis, though this may change as a more holistic, integrated assessment methodology is currently under development [82]. Commercial tools are available as well—for example DNV GL's microgrid optimizer tool [83]—but are often proprietary and used in-house. Other tools have been developed to analyze individual microgrids, for example the dispatch optimization tool developed by Energy+Environmental Economics (E3) and Viridity for the University of California, San Diego (UCSD) microgrid [84].

2.2. Other studies related to microgrids

In addition to models, which are the main interest for this paper, many other studies are relevant to the design, operation, policy support and future evolution of microgrids. We see these falling broadly into four categories, each of which we illustrate briefly.

First, there are empirical studies. These include studies on overall trends in microgrid investment [24], [33], [85]—trends that we use to identify the characteristics of the iconic microgrids that we present here. The market for microgrids is expanding, forecasted to grow, and moving toward full commercialization. North America is the leading market. At present, installations at military facilities, campuses, and remote communities comprise the majority market share, but grid modernization and resiliency are opening new commercial markets oriented toward public assets and critical facilities [86], [87]. The majority of extant microgrids employ conventional generation (that is, fossil fuel-based), but the use of CHP and renewables is forecasted to increase, especially as microgrids emerge as tools to integrate renewables. In addition to empirical studies focused on overall trends, there is empirical research focused on particular microgrids, notably individual case studies [84]. San Diego Gas & Electric's (SDG&E)'s microgrid at Borrego Springs stands out as a microgrid system that combines elements of research and development with commercialization [88].

Second, many studies have focused on particular technologies that are pivotal to microgrids. These include studies which survey generally the prevailing DERs that could be integrated in microgrids [38], [89], their costs and benefits [90], and adoption [91]. They also include independent studies of specific technologies, such as energy storage—for example the widely used EPRI analysis of battery storage technologies [92], [93], analysis of battery storage costs [30], and analysis of energy storage markets

[94]. A substantial literature has also emerged around the special issues associated with remote, rural electrification and the opportunities for microgrids in solving the "last mile" problem for those systems [95].

Third, some studies have attempted to look at the larger grid as a whole system—thus inevitably including some attention to particular current or possible future components, such as ubiquitous microgrids and DERs such as rooftop solar PV systems. Integration studies quantify challenges and impacts and how best to incorporate distributed resources into the electric grid [96], [97]. Other studies present visions for the "grid of the future", where distributed resources and microgrids play a central role in a dynamic grid [19], [98].

Fourth are the many studies that look at regulatory issues and opportunities. Several papers discuss regulatory barriers [25], [99]–[101]. In most cases current regulation supports a centralized model of generation and distribution—microgrids challenge this framework and so regulatory barriers to deployment are common. Discussion and assessment of the legality of microgrid ownership models—a potential first step toward developing systemic rules for adoption—is ongoing in several states, for example California [100], Maryland [20], Massachusetts [102], [103], and New York [99]. Microgrid adoption is in some instances practicable already under current law—for example the single-property single-owner model that we analyze in the present study. However, the boldest visions for microgrid deployment envision systems that would require transformative changes: new definitions and/or exclusions to electrical corporations, revisions to traditional exclusive franchise rights, access to public rights-of-way for laying wires and other microgrid infrastructure, and local retail markets. For those reasons, there is momentum behind a greater push for transformative change to the current distribution system to one comprised, in part, of high penetrations of distributed generation and microgrids [19], [25], [98], [104].

3. Building a Tool for Assessing Business Models

Building a tool for studying microgrid business models has required efforts on two fronts, which are the main contributions of this paper. First we identify the characteristics of prototypical microgrids aligned with forecasted market growth for microgrids. We term these *iconic microgrids*. Second, we recalibrate DER-CAM and customize it in ways that make it particularly useful for today's market settings in California—while reporting those parameters in ways that allow for ready adjustment to other markets. We address each in turn here.

3.1. Three iconic microgrids

Within the US, the market for microgrids is nascent and dominated at present by military and campus installations. These are large systems covering many buildings and operated by a single owner. From 2015-2020, forecasts suggest such installations will continue to constitute the majority of total microgrid capacity, but two other market segments are expected to grow as well: facilities that have particularly great need for reliability (for example, hospitals) and commercial buildings. Microgrids developed for the former, which include critical infrastructure, are forecasted to grow fastest among market sectors. The military and university campus market segments are forecasted to grow by 142 and 115 percent, respectively; the city/community and public institution segments, by 199 and 228 percent; and the commercial segment, by 94 percent [33].

We create three iconic microgrids to capture these three existing and forecasted market trends. We term the three cases the *large commercial*, *critical asset*, and *campus* microgrids[1]. For each of these three types of microgrids we construct load profiles that consist of electric, space heating, water heating, cooling, and natural gas loads. In line with common regulatory rules for electric utilities, we assume microgrids are installed behind-the-meter within the boundaries of a single property and with a single owner (regulatory rules that constraint adoption to this framework are common to many jurisdictions [11]). Figure 1 presents the load profiles for a weekday in February along with annual energy consumption. A complete set of profiles is reported in the supplemental information.

We use the US DOE data set of commercial reference buildings to create load profiles for the three iconic microgrids [105], [106]. This data set comprises hourly annual load profiles for electricity, electric cooling, electric heating, natural gas, and gas heating, and consists of sixteen building types that represent approximately 70 percent of all commercial buildings in the US. Thermal loads are available for sixteen locations encompassing sixteen climate zones—we use climate zone 3B-CA, which includes Los Angeles, California. Building types include offices, schools, restaurants, hotels, and a hospital, among others.

The DOE data have been available since 2011. The Grid Integration Group at LBNL has used DER-CAM in combination with the DOE reference building data set to study the economic benefit of particular distributed technologies across multiple economic and climate conditions [107], [108]. For example, they analyzed thermal energy storage in four cities with different electric tariff structures and climates to determine factors that most impact the economics of investment [109]. Systematic studies such as these are valuable because they provide insight into adoption trends for specific DERs across a range of important parameters. The present work is similar in this regard. A central difference, though, is that we extend this type of analysis to microgrid business models generally, and focus on drivers of investment cases and trends in microgrid adoption rather than on specific technologies, electric tariffs, etc. The present work adds to the literature by aligning iconic microgrids with forecasted market growth.

By combining the rich DOE data into three types of building clusters—each served by a microgrid—we hope to facilitate a common core of research and promote more systematic analysis of microgrids. We have checked the DOE data against real-world conditions at UCSD, which operates a large microgrid to supply electricity and thermal energy to the campus [37]. Monitoring systems for electrical loads within the microgrid are ubiquitous and acquired data has high resolution—typically one minute or smaller. Individual, room-level, building-level, and campus-wide loads are monitored. We use this abundance of data to verify the DOE reference building electric load profiles.

[1] Greentech Media distinguishes between five microgrid segments: military, university, city/community, public institution, and commercial. Each of our three iconic microgrids fall into one or two of these segments—the commercial building aligns with the commercial segment, the critical asset with the city/community and public institution segments, and the campus with the military and university segments.

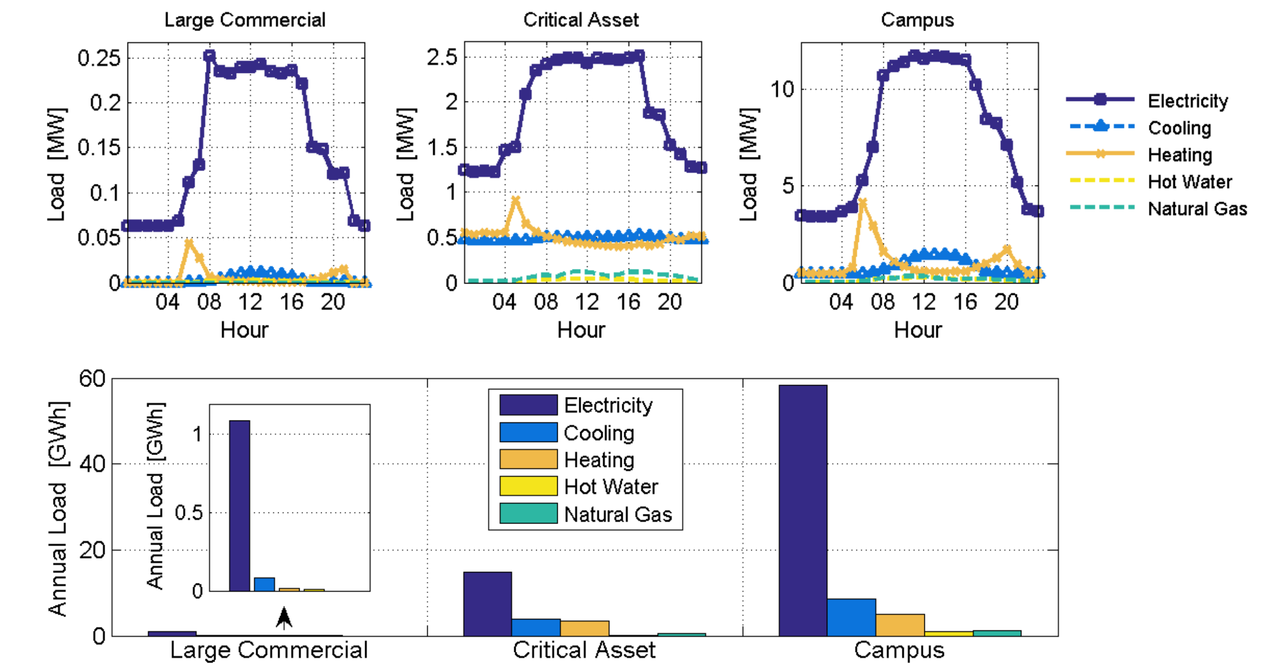


Figure 1: Load profiles are presented for a February weekday (top). The load shapes are representative of weekdays throughout the year. Weekend days have a similar base load but do not peak so significantly during the day. Annual energy consumption is presented for all end-use loads (bottom). Note variable y-axis scaling for the time series and constant y-axis scaling for annual energy consumption.

Large commercial building customers include, for example, large box stores like Walmart or Costco, as well as office buildings. These customers consume electricity primarily but may also have varying demand for heating and cooling. As such, CHP investments may not be preferable. Of the three, this class consumes the least energy but is the most common. We model the large commercial microgrid in DER-CAM using the medium office from the set of DOE commercial reference buildings.

Critical assets include hospital complexes, community centers, or data centers. The critical asset class is defined by its high demand for reliability—a large portion of the load is deemed critical and must be maintained during outages. High capital costs for on-site generation are therefore required to reliability supply the peak critical load, which may be large relative to base load consumption. Distinct from the other two microgrids, the critical asset consumes thermal energy (heating and cooling) relatively constantly throughout the day and has the smallest load factor (the ratio of load at a given moment to the day's peak load). Such load shapes favor CHP investments. We model the critical asset microgrid in DER-CAM as a hospital complex—that is, a hospital facility with other ancillary facilities. Quantitatively, we construct it as the sum of the hospital, quick-serve restaurant, and outpatient facility from the set of DOE commercial reference buildings.

Campuses include college campuses or military bases. Campuses are geographically large and lay within a single ownership boundary. Typically they have no public roads within the service territory since most US regulatory law prevents non-utilities from running power lines across public roadways. Consequently they comprise an aggregation of many residential, commercial, and industrial load profiles. The campus class has a large thermal demand, and of the three has the largest demand and volumetric consumption.

We model the campus microgrid in DER-CAM as a college campus. Quantitatively it is the sum of the small office, medium office, two large offices, three stand-alone retail centers, three supermarkets, four midrise apartments, two primary schools, two secondary schools, one strip mall, one quick-serve restaurant, and one full-serve restaurant from the set of DOE commercial reference buildings.

In general, the timing of the customer's peak electric load, load factor, and magnitude of thermal loads drives the economic benefit derived from microgrid adoption. For example, load magnitude and shape may make solar PV adoption advantageous, while the combination of electrical and thermal loads may make CHP adoption advantageous. We recognize that the three iconic microgrids will not capture every commercial and/or industrial customer, but they do capture a majority of customers within microgrids segments with the most significant growth forecasts. Though each customer's pattern of energy consumption is ultimately unique, by using two veritable sets of building load data we believe these microgrids represent the prototypical customer within the three important microgrid markets (commercial buildings, critical assets, campuses).

3.2. Model parameterizations

This section lists key parameterizations used to model the three iconic microgrids, which Table 1 presents. We use DER-CAM version 4-4.1.1 and configure the models using present-day parameters for interconnection in California. We modify parameters to make the interconnection specific to the local utility, as well as those parameters that are most critical to microgrid business models: electric tariffs (which include volumetric, demand, and standby charges), natural gas price, cost of carbon, cost of solar PV, and cost of electric storage. We leave numerous parameters as defaults—for example, location-based parameters (which are configured for California) such as ambient temperature and solar insolation, grid and technology emission rates, the cost and performance of conventional generators and thermal recovery, and the performance of energy storage. A full list of modified parameters is included in the supplemental information.

The hourly time series of end-use loads—presented in part in Figure 1—consist of weekday and weekend days, which we assign using calendar year 2014. A typical month has 20-23 weekdays and 8-10 weekend days. For generality we do not consider peak days.

As is standard with DER-CAM, we model two customers types (each with the same set of loads) for each iconic case—a macro grid customer, who supplies all load by purchasing electricity and fuel from the local utility, and a microgrid proprietor, who invests in DER technologies to self-supply some portion of load. We model each microgrid as interconnected to the distribution system and take SDG&E as the local utility using the commercial tariff Schedule AL-TOU. That electric tariff structure, as is common across many utilities, imposes demand charges (non-coincident, summer on-peak, and winter on-peak) and volumetric charges (summer and winter on-peak, semi-peak, and off-peak). The volumetric charge is based on the total electricity consumption and the demand charge on the maximum power consumption. The microgrid proprietor invests in DERs that supply load with the goal of mitigating these tariff charges.

The microgrid proprietor is in addition subject to two further tariffs: a standby charge per Schedule S and departing load charge per Schedule E-DEPART. The standby charge is a dollar-per-kilowatt charge based on the capacity of conventional generators installed within the microgrid—the charge is designed to reflect the maximum load that the microgrid might draw from the utility if all those local generators were to fail. It can be substantial and, as we will show, often impacts the economically optimal microgrid configuration. Departing load is the portion of load for which the customer self-generates to replace grid purchases. Its associated charge (approximately 0.005-0.015 $/kWh) is small relative to other tariff charges, and moreover specific to the three investor-owned utilities in California [110]. For generality we neglect it.

Several exogenous parameters are important for analyses of microgrid economics. We assume that the cost of capital is 7 percent—and use the same rate for discounting calculations. The price of natural gas varies by region and time of year, among other factors. We use a price of 8 $/mmbtu based on sales to commercial customers in California [41]. We use 12 dollars per metric ton carbon dioxide equivalent ($/MT CO_2e) for the carbon price based on the price of California Carbon Allowance futures [111].

DER-CAM contains an extensive database of conventional generators, including reciprocating engines, microturbines, and gas turbines—both with and without thermal recovery. Costs, performance, emission rates and efficiencies are considered. In the models, conventional generators are fired with natural gas. The database includes units in discrete sizes ranging between 60 and 1000 kW. The role of CHP, as we shall show, is particularly important for microgrids for its potential to increase energy efficiency.

The cost of solar PV and electric storage is decreasing rapidly. With decreasing costs we foresee—in some instances—adoption of low-carbon microgrids based around these technologies. To capture this important trend, we use current costs for non-residential rooftop PV systems [29] and a projected cost estimate for electric storage. Our storage cost aligns with estimates of current and projected costs [30], [112], [113].

The models in the present study are conservative is many regards. We do not include several sources of other revenue—for example from net metering or incentive programs such as FIT programs , production tax credits, and investment tax credits. We neglect state incentives as well, such as the Self-Generation Incentive Program (SGIP) in California.

Table 1: Select model parameterizations

	Parameterization	Units	Source/Comment
Tariff Parameters			
Tariff	-	-	SDG&E Schedule AL-TOU, EECC
Voltage service	Primary	-	
Standby charge	13.76	$/kW	SDG&E Schedule S
Departing load charge	0	$/kWh	
Market Parameters			
Interest rate	7	%	Lower medium grade corporate bond rate
Natural gas price	8	$/mmbtu	Commercial retail price in California
Cost of carbon	12	$/MT CO_2e	California Carbon Allowance futures
DER Parameters			
Solar PV capital cost	2390	$/kWac-peak	Solar Market Insight Report 2015 Quarter 2
Electric storage capital cost	350	$/kWh	Nykvist and Nilsson 2015; Economics of Load Defection by Rocky Mountain Institute, 2015;

		Energy Storage Study by AECOM, 2015
Energy Revenue Sources		
Net energy metering	No	Expiring July 1, 2017
Feed-in tariff	No	Exports and sales are restricted to develop a baseline business model based solely on avoided energy costs.
Energy sales	No	
Incentives		
Investment Tax Credit	No	Incentives are neglected to develop a baseline business model based solely on avoided energy costs.
Production Tax Credit	No	
California SGIP	No	

Parameterizations include also important constraints. For instance, the models constrain the area in which solar PV can be installed, which we term the *solar PV space constraint*. Assuming rooftop systems are installed, the available installation space depends on building size and the number of buildings. We use approximations based on real-world numbers. We note that this constraint often affects model results (solar PV is often invested in maximally), but we nevertheless include it. We also quantify the economic impact of removing it.

The capability of a microgrid to improve reliability (by islanding to maintain power during macro grid outages) is a primary driver of forecasted microgrid market growth. Such improvements are typically monetized by assigning a value of lost load (VOLL), but estimates of VOLL are difficult, often general, and have large variance. One can prescribe a VOLL in DER-CAM, and to realize that benefit DER-CAM enforces an investment constraint—which we term the *minimum investment constraint*—that is closely related to the size and configuration that is needed for islanding and reliability that meets peak critical electric load, assuming one battery charge/discharge cycle per day and an average annual solar insolation. This constraint does not guarantee perfect reliability, nor does it guarantee the ability to island during all hours of the day and all days of the year. Rather, it approximates the investment required to island generally—an outcome designed to approximate the estimated microgrid configuration with reasonable DER capacities but with full appreciation that further analysis and modeling refinement would be needed when designing any particular system. Because of this approach, standard in the literature, here we do not monetize reliability (negatively or positively) in the models. Nevertheless we do enforce the minimum investment constraint.

4. Results

DER-CAM computes the least cost combination of DERs (type and capacity) and the hourly operation over the first year of implementation. We term the optimal combination of DERs the *optimal configuration* and the hourly first year operation the *optimal operation*. Together, the optimal configuration and optimal operation comprise the *optimal system*.

We run the model for a typical weekly load profile—which includes weekday and weekend profiles—for each of 12 months. We make such calculations for two types of customers. One is the *microgrid proprietor*—who adopts a microgrid and supplies end-use load with a combination of power generated on-site, thermal energy recovered on-site, and/or power and natural gas purchased from the utility. The other, for comparison, is a *macro grid customer,* who supplies the same load profile entirely through purchases of power and natural gas from the utility.

4.1. Baseline model runs

We model a baseline case for each microgrid proprietor. The optimal configuration is given in Table 2, which distinguishes investment in conventional generators (fired with natural gas), renewables, energy storage, and thermal units that supply the thermal loads directly. We also distinguish the use of CHP-enabled generators—which supply power and thermal loads within the microgrid—because they can greatly improve energy efficiency and are thus often pivotal to microgrid systems. The supplemental information provides a detailed breakdown of investment by individual technology and unit.

Table 2: Optimal microgrid configuration for the baseline model runs

	Large commercial	Critical Asset	Campus
Conventional generators			
Generators without CHP	150 kW	750 kW	4250 kW
Generators with CHP	-	1650 kW	6250 kW
Renewables			
Solar PV	200 kW	1250 kW	3100 kW
Energy storage			
Electric storage	230 kWh	20 kWh	850 kWh
Thermal units			
Absorption chiller	-	350 kW	1400 kW
Cold storage	220 kWh	-	3800 kWh

Figure 1 presents the optimal operation for microgrid proprietors during representative winter and summer months (dispatch for all 12 months is presented in the supplemental information). The models invest in and operate DERs to mitigate demand and volumetric charges, the largest costs to the macro grid customer. In general, the aggregate capacity of the optimal configuration is sized to supply peak electrical demand—to facilitate islanding per the minimum investment constraint, peak load shaving, and to minimize volumetric charges by displacing almost all grid purchases. What differs across the three iconic microgrids is not the sizing of DERs relative to the peak load—instead, it is which DERs (conventional generators, CHP, solar PV, and electric storage) comprise the optimal configuration. Grid purchases play a small base role in some configurations and months.

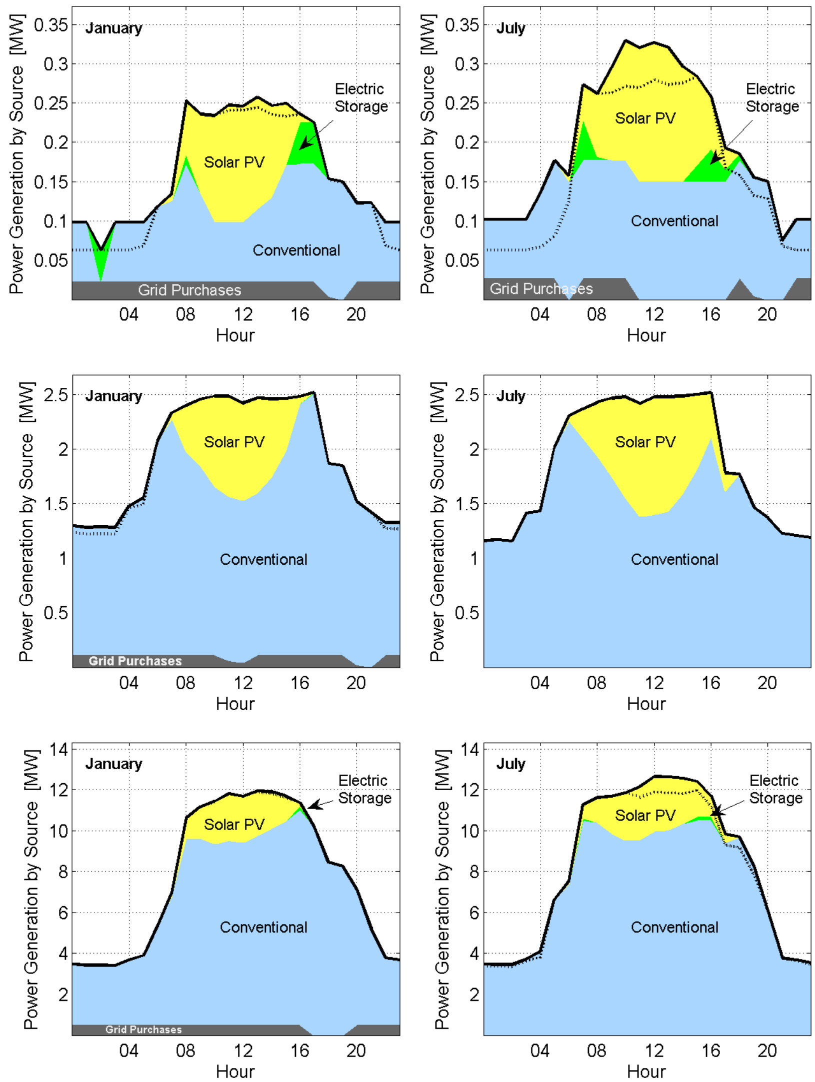


Figure 2: The optimal dispatch for representative winter and summer months for the three iconic microgrids—large commercial (top), critical asset (middle), and campus (bottom)—shows how the microgrid supplies the electrical load with a combination of grid purchases and on-site generation from conventional generators, solar PV, and electric storage. The microgrid load is denoted in solid black and the macro grid customer load in dashed black. The two are different because the microgrid consists of DERs that consume additional electricity—see, for example, electric storage in the large commercial microgrid. Electric storage is shown in green when discharging and as an adder to the macro grid customer load when charging.

While the details of each configuration are complex, the broad patterns and highlights of each iconic microgrid configuration are as follows:

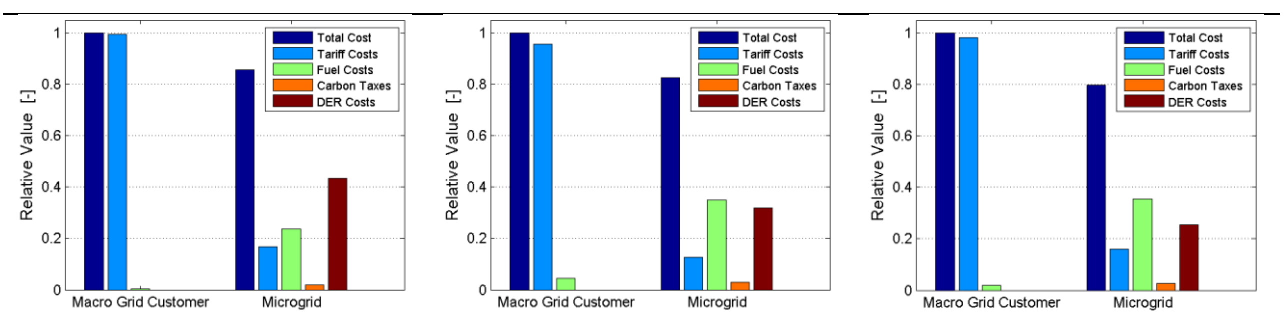
- For the large commercial microgrid, conventional generators supply base load and solar PV supplies peak load. Electric storage further supplies peak load when solar PV output is unavailable, especially during winter evenings. Cold storage provides chilled water during off-peak hours. The thermal demand is relatively small and so the model does not invest in CHP.

- For the critical asset microgrid, base load is supplied by conventional generators, two-thirds of which is CHP-enabled to meet the relatively large thermal demand. An absorption chiller further supplies the thermal load via heat recovery. Solar PV supplies peak load and electric storage supplies a small amount of shoulder load between the on-peak and off-peak periods.
- For the campus microgrid, base load is supplied by conventional generators, 60 percent of which is CHP-enabled to meet thermal demand. An absorption chiller further supplies the thermal load via heat recovery and cold storage provides chilled water during off-peak hours. PV supplies peak daytime load and electric storage further provides peak load when PV output is small or unavailable.

The primary driver underpinning adoption is the potential to utilize relatively inexpensive natural gas. The models forego grid purchases and instead prefer on-site generation from conventional sources to supply the base electrical load. Gas prices are low, carbon emissions are comparable with grid purchases, and grid-supplied electricity in California (the source of the assumptions in Table 1) is relatively expensive during both peak and non-peak periods. Further, the combination of electric and thermal loads makes CHP adoption favorable. The critical asset and campus microgrids install CHP to integrate electric and thermal loads and thus increase system efficiencies. In doing so, they reduce electricity and fuel purchases for direct heating and cooling.

The optimal investment case comprises solar PV for each microgrid. Peak load coincides with solar PV output, favoring its investment. Moreover, available space for solar PV constrains model results in two cases—for the critical asset and campus microgrids. The large commercial microgrid uses 33 percent of available space and is unaffected; the critical asset and campus microgrids use all available space. When unconstrained, the models invest in 40 percent (1750 kW constrained, 1250 kW baseline) and 177 percent (8600 kW unconstrained, 3100 kW baseline) more solar PV, respectively. Such large solar PV installations are cost effective because of the large daily peak in load and the coincidence of peak load with solar noon.

For each customer type we compute the *total energy cost* for the first full year of operation—presented in Figure 3 for microgrid proprietors and the macro grid customer who supply the same electric and thermal loads entirely through grid purchases. The two customer types are subject to different sets of competing costs. The macro grid customer pays electricity and gas charges per applicable tariffs ("tariff costs" and "fuel costs"). The microgrid proprietor pays the same charges as well as standby charges for on-site generation, in addition to the annual amortization for the capital investment needed to build the microgrid ("DER costs"). DER costs include also microgrid operations and maintenance costs. All customers pay carbon costs ("carbon taxes"), although those that buy electricity and gas from the grid pay those costs indirectly as part of their electric tariff. These costs are summed to calculate the total energy cost for each customer, and we find that in all cases microgrid adoption reduces that cost relative to the macro grid customer.



Large commercial Critical asset Campus

Figure 3: The disaggregation of the total energy cost is presented for the first year of operation for the macro grid customer and microgrid proprietor. Microgrid adoption significantly shifts the dispersion of costs—from tariff costs to DER and fuel costs. In doing so it reduces the total energy cost—by 14, 17, and 21 percent for the large commercial, critical asset and campus microgrids, respectively. Costs presented are normalized to the macro grid customer's total energy cost.

4.2. Simple sensitivities

Following on the baseline models, we run numerous simple sensitivity models, in which we hold constant the optimal configuration from the baseline run, vary a single parameter, and permit the models to re-optimize operation; in these sensitivity studies the model does not re-optimize the generation mix, which we present in section 4.3. Many parameters affect the total energy cost of the microgrid, each with varying degree depending on the particular microgrid system. For example, the business model for a low-carbon microgrid will depend largely on the capital costs of solar PV and energy storage—costs which have real variance depending on, for instance, manufacturer, chemistry, and/or the type and location of the installation. Simple sensitivity models therefore help to quantify the robustness of the business model by quantifying the change in total cost to plausible variation in key parameters.

In general, DER costs, tariff costs, and market parameters are key drivers of the total cost—DER costs vary over time, mostly declining with technological advances; tariff costs are updated often and prices and structures vary by utility; gas prices fluctuate and vary seasonally and/or geographically; and carbon costs are imposed jurisdictionally and vary. We run sensitivity models for a subset of these costs and parameters. Since the costs of specific DER technologies underpin investment we analyze the interest rate, capital and O&M costs of conventional generators, as well as the capital cost of solar PV, electric storage, and thermal storage. The costs of solar PV and electrical storage are falling relatively rapidly. We analyze the price of natural gas because it is volatile relative to other parameters such as tariff and DER costs and also because the optimal microgrid systems in section 4.1 consist primarily of gas generators. We choose the cost of carbon because it a key mechanism to achieve emission reduction and clean energy targets. Lastly, we choose the electrical load to capture load growth within the microgrid and thermal loads to capture a range of other climate zones in the US. We discuss the specifics of each in turn.

We vary the interest rate -/+25 percent from the nominal rate of 7 percent, generating the range 5.25-8.75 percent. 7 percent reflects a typical discount rate for lower medium grade (BBB- to BBB+) corporate bonds at the time of this publication; the sensitivity range further covers high-yield and upper medium grade bonds.

We vary the cost of carbon from the nominal cost of 12 \$/MTCO_2e -100/+1000 percent (0-132 \$/MT CO_2e) to capture the 95th-percentile cost for the out-year 2020 (129 \$/MT CO_2e) per the US Office of Management and Budget (OMB) technical support document for the social cost of carbon [114]. At the time of this work the price of California Carbon Allowance futures was trading between 12 and 13 \$/MT CO_2e.

We vary the natural gas price from the nominal price of 8 \$/mmbtu -50/+100 percent (4-16 \$/mmbtu). This sensitivity range is based on Annual Energy Outlook 2015 (AEO2015) forecasts for 2030 and captures the full range of projected Henry Hub spot prices (4 \$/mmbtu in the “High Oil and Gas Resource” scenario and 8 \$/mmbtu in the “High Oil Price” scenario) [115] while further allowing for a range of retail prices which vary according to local natural gas infrastructure spending.

We vary the volumetric charge (using the 2013 average retail price for commercial customers in California as the baseline) -45/+15 percent to capture the 5th- and 95th-percentiles for the average retail price of electricity for commercial customers across all 50 states and the District of Columbia during the period 2013-2033, assuming an average increase of 0.6 percent per year pursuant to the AEO2015 “Reference case” scenario [115]. We project the price to 2033 to capture variation over the 20-year plausible lifetime of the microgrid.

The EIA frequently publishes data on monthly average retail electricity prices (through the AEO) based on collected utility revenues and sales—a metric that amalgamates all utility charges—but does not report demand charges or standby charges singly. Surveying the range of demand and standby changes across utilities to generate a sensitivity range is not straightforward because those charges are closely tied to volumetric charges in the ratemaking process, and, further, it is unclear how to normalize utility charges against the volumetric charge. As such, for simplicity we vary the demand and standby charges -45/+15 percent to align with the variation in volumetric charge.

We vary the capital cost and O&M cost of natural gas-fired generators -20/+10 percent based on cost projections for 2010-2030 for small (<1 MW) generators. Capital costs for small reciprocating engines and microturbines are expected to decline 20 percent over the next 20 years due to technology advances and market competition, while the 10 percent increase considers potential emissions treatment equipment costs for compliance with more stringent emissions regulations [116]. Though both capital and emissions treatment equipment costs vary by generator type and capacity, for generality we apply the -20/+10 percent sensitivity range across all generator types.

We vary the capital cost of electric storage from the nominal cost of 350 \$/kWh by -50/+300 percent (175-1050 \$/kWh) to capture existing and projected market trends. The present-day hardware cost for battery storage ranges widely across manufacturers (and chemistries)—from 350 to >2000 \$/kWh (lead-acid may be as low as 200 \$/kWh while lithium-ion may be 500 \$/kWh) but are forecasted to fall sharply over the next 5-10 years [117]. For reference, as of 2015 Tesla Motors sells the larger of its two Powerwall stationary battery storage products for 350 \$/kWh (though the offering excludes inverter and soft costs).

The cost of thermal storage for hot and/or cold water (if adopted) is a negligible component of the upfront capital cost. The water heating load of the iconic microgrids is similarly negligible relative to the electrical load. Consequently we vary the cost of thermal storage nominally from the nominal cost of 50 \$/kWh by -20/+20 percent (40-60 \$/kWh) to consider potential technology advances or unforeseen policy changes affecting thermal storage.

We vary the turnkey cost of solar PV from the nominal cost of 2,390 \$/kW by -50/+50 percent (1195-3585 \$/kW). The sensitivity decrease nears the DOE SunShot Initiative goal of 1 \$/W installed cost, while the sensitivity increase nears the cost of smaller rooftop solar PV systems (5-10 kW), which are classified as “residential” and 3,740 \$/kW in the 2015 Q1 SEIA US Solar Market Insight [29]. The 2,390 \$/kW cost taken as the nominal cost assumes large rooftop installations near 200 kW.

We vary the magnitude of the electrical load by -20/+20 percent to capture both potential load growth and energy efficiency measures implemented over the lifetime of the microgrid. The load growth scenario assumes an annual growth rate of 1 percent (per EIA forecasts) through the 20-year lifetime of the microgrid; the load reduction scenario assumes an annual growth rate of -1 percent due to adoption of energy efficiency technology advances.

We vary the magnitude of thermal loads by -50/+50 percent to capture deviations from the nominal climate zone 3B-coast (a moderate climate that requires relatively little building heating and cooling and which covers the coast of southern California). Climate zones in the US range from 1A (hot and humid; for example Miami, Florida) to 8 (cold; for example Fairbanks, Alaska).

Figure 4 presents the simple sensitivities for the three iconic microgrids. For each sensitivity model run, we hold fixed the optimal configuration from the baseline model run and permit the model to re-optimize operation.

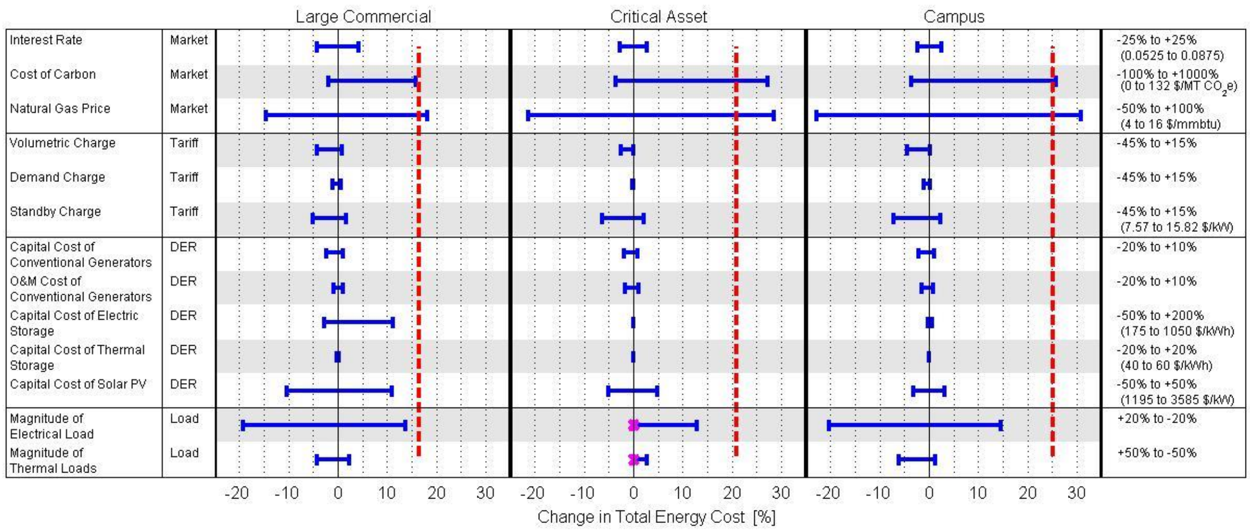


Figure 4: Simple sensitivities are presented for the three iconic microgrids—large commercial (left), critical asset (center) and campus (right)—and show the change in total energy cost due to variation in model parameters. The red dashed line denotes the "parity point"—the cost increase that produces a total energy cost equal to that for the macro grid customer. We note that for some market parameters—such as the natural gas price and carbon cost—the parity point shifts because variation in those parameters affects electricity rates for the macro grid customer, though such shifts are not noted. The models do not converge in two instances, which are marked in purple—sensitivity models for the magnitude of electrical and thermal load for the critical asset microgrid do not meet the minimum investment constraint because the fixed configuration does not have the capacity to supply the increase in critical load.

Several trends in the sensitivity results are common across the three microgrids. First, sensitivities to volumetric and demand charges are relatively low because the microgrids primarily self-generate. Second, sensitivities to the carbon cost and fuel price are high and exceed sensitivities to DER costs. In other words, plausible variations in operating costs (such as would be paid for carbon taxes and fuel) may drive the total energy cost to a greater degree than plausible variations in capital costs (cf. the relative magnitude of DER and fuel costs in Figure 3). Third, the sensitivity to the electrical load is large. During most hours the microgrids have reserve generation (conventional generators are sized to meet the peak critical load and do not run at 100 percent output during non-peak hours), which they use to supply the majority of load growth, thereby reducing further the total energy cost relative to the macro grid customer. This sensitivity is highly dependent on the volumetric charge and gas price—if volumetric charges are sufficiently low or gas prices high, the models will instead supply load growth with grid purchases. Note that variation (positive vs. negative) is reversed in Figure 4 for the electrical and thermal load sensitivities—load reductions cause cost increases relative to the base case microgrid customer.

The range of total energy cost deviations from sensitivities shows that the business model is robust. Only extraordinarily high values for the carbon cost (approaching 100-120 \$/MT CO_2e) and fuel price (approaching 12-16 \$/mmbtu) make microgrid adoption uneconomical. Yet high carbon taxes and fuel prices would also be expected to increase electric rates commensurately and move the parity point to the right.

4.3. Strategically important uncertainties and business models

We now turn to greenfield sensitivity analyses, in which we permit the models to re-optimize both the configuration and operation. This form of sensitivity analysis, which is computationally more intensive, begins with identification of four uncertain variables that have large strategic effects on the business model for microgrid adoption: natural gas price, electric storage cost, electric tariff charges, and carbon costs. We identified these four strategically important variables in several ways. First, the simple sensitivity models indicate that the gas price and carbon cost are important to the business model because results are sensitive to these parameters. Moreover, markets are driving changes in these parameters—storage costs are declining rapidly and gas prices are inherently variable. Second, tariff charges ultimately drive the optimal configuration by favoring (or not) peak shaving and on-site generation—the configuration of the microgrids is dominated by attention to the need to mitigate volumetric and demand charges while considering standby charges. Moreover, tariff charges and structures vary generally by utility and region and so it is important to capture the range of charges employed across utilities and regions. Lastly, we look at the cost of carbon because its adoption might prove a key tool for decarbonization in California, and perhaps elsewhere in future years.

4.3.1. Natural gas price

Figure 5 presents the total energy cost to the macro grid customer and microgrid proprietor for varying natural gas price (\$4-16/mmbtu), and also the breakdown of energy provision by source for the microgrid.[2] Justification for variation in the natural gas price is as discussed in section 4.2 for the simple sensitivity analyses.

Both the macro grid customer and microgrid proprietor purchase fuel from the utility to meet the natural gas load; hence the total energy cost increases with natural gas price for both customers. Nevertheless, across the full range of gas prices, microgrids incur smaller net energy costs when compared with grid purchases—with the largest differences occurring when natural gas prices are low. The models invest in conventional generators when prices are low and, as prices increase, replace conventional generation with renewable sources and grid purchases, a transition that decreases the difference in total energy cost between the two customers. Beyond 9 \$/mmbtu the large commercial

[2] We increase the volumetric charge as the natural gas price increases to account for a corresponding increase in natural gas-generated wholesale electricity. We increase only the generation portion of the volumetric rate and scale the increase by the fraction of wholesale electricity generated from natural gas plants in California (45 percent at the time of this work).

microgrid adopt a low-carbon configuration and thereby insulates itself from further increases in the gas price. The critical asset and campus microgrids, on the other hand, see shrinking net cost saving from microgrids as gas prices increase—they do not transition to low-carbon configurations, but rather revert to grid purchases. Higher gas prices make it harder for these microgrids to utilize one of the chief advantages of local production: the on-site use and storage of thermal energy via CHP.

For all microgrids there is a sharp transition from conventional generation to grid purchases. For the large commercial microgrid this transition occurs at 7-9 $/mmbtu; for the critical asset microgrid, at 11-13 $/mmbtu; and for the campus microgrid, 9-11 $/mmbtu. These transition points have significant implications for the optimal configuration and subsequent business case.

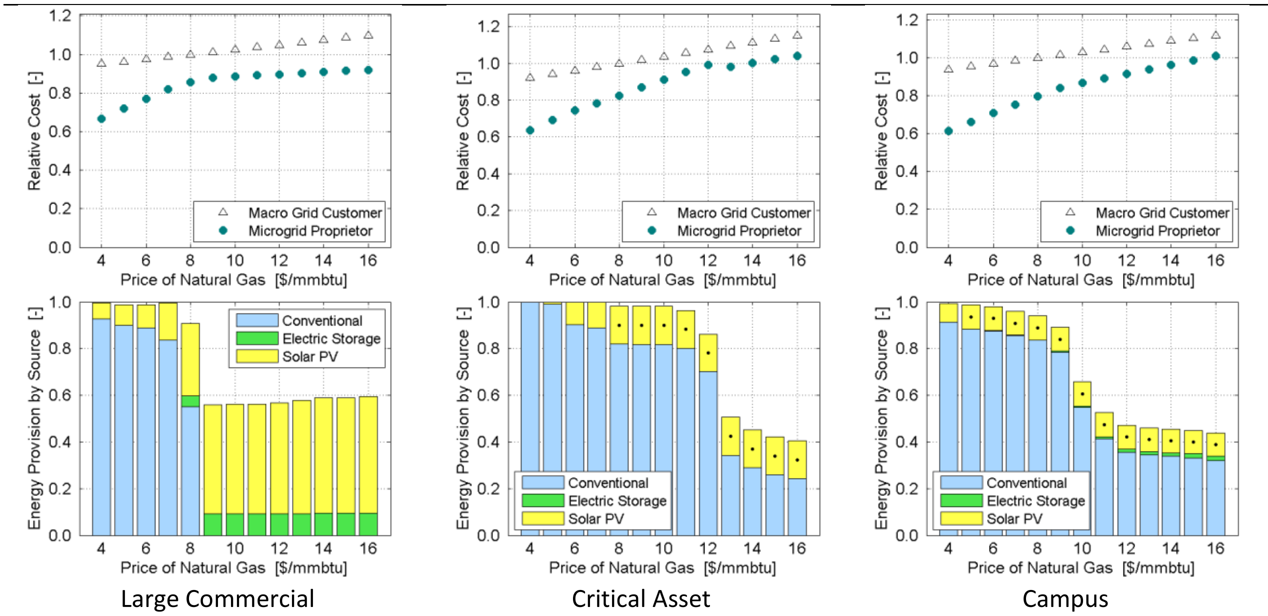


Figure 5: The total energy cost is presented for the macro grid customer and microgrid proprietor (top). Costs are normalized by the total energy cost of the macro grid customer for the nominal natural gas price (8 $/mmbtu). Energy provision by source is presented for the microgrid proprietor across variation in natural gas price (bottom). Each bar is a separate model run and the remaining unfilled portion of the bar represents grid purchases. A black dot in the bar for solar PV provision denotes that solar PV installations are space-constrained.

4.3.2. Cost of grid purchases

Volumetric and demand charges are the two tariff charges most important for distribution-level microgrids. The magnitude and daily variation in these charges often drives the business case for microgrids—for example large demand charges drive peak shaving schemes, and the same is true for high on-peak volumetric charges and load shifting. Figure 6 presents the total energy cost to the macro grid customer and microgrid proprietor for varying volumetric charge as well as the breakdown of energy provision by source for the microgrid. Volumetric rates are varied fractionally from 0.4-1.4 in increments of 0.1, where the unity fractional rate is the nominal rate in the electric tariff. All charges in the tariff are varied concurrently and justification for variation is as discussed in section 4.2 for the simple sensitivity analyses.

We find that volumetric rates greatly affect the total energy cost and the optimal configuration. Further, as with variation in gas price, sharp transition points exist in which conventional generation and grid purchases are substituted. When volumetric rates are low (less than 50 percent of present rates), microgrid costs exceeds that of the macro grid customer, and there is no economic benefit to adoption. At rates greater than 50 percent of nominal, however, we observe an economic benefit that increases with increasing rates. For each microgrid, there are scenarios in which the microgrid self-generates to supply nearly 100 percent of load. Most notable, though, is the fractional volumetric rate at which this occurs. In all cases, electricity rates today make near 100 percent self-generation economical. Grid purchases become economical only when rates near 0.6-0.9 (depending on the microgrid), and business are more robust for the larger microgrids.

The set of optimal configurations fits largely within two domains, separated by the transition point. For volumetric rates <0.9, the large commercial microgrid adopts a low-carbon configuration consisting of solar PV and electric storage, but adopts conventional generators for rates >=0.9, which remain central to the business model thereafter while displacing low-carbon resources. Similar transitions occur for the critical asset and campus microgrids—for rates 0.6-0.8 and 0.7-0.9 respectively. However the investment case for these microgrids remains with conventional generators. The range over which the models invest in gas generation is wide and reinforces natural gas technologies as the bedrock of investment cases.

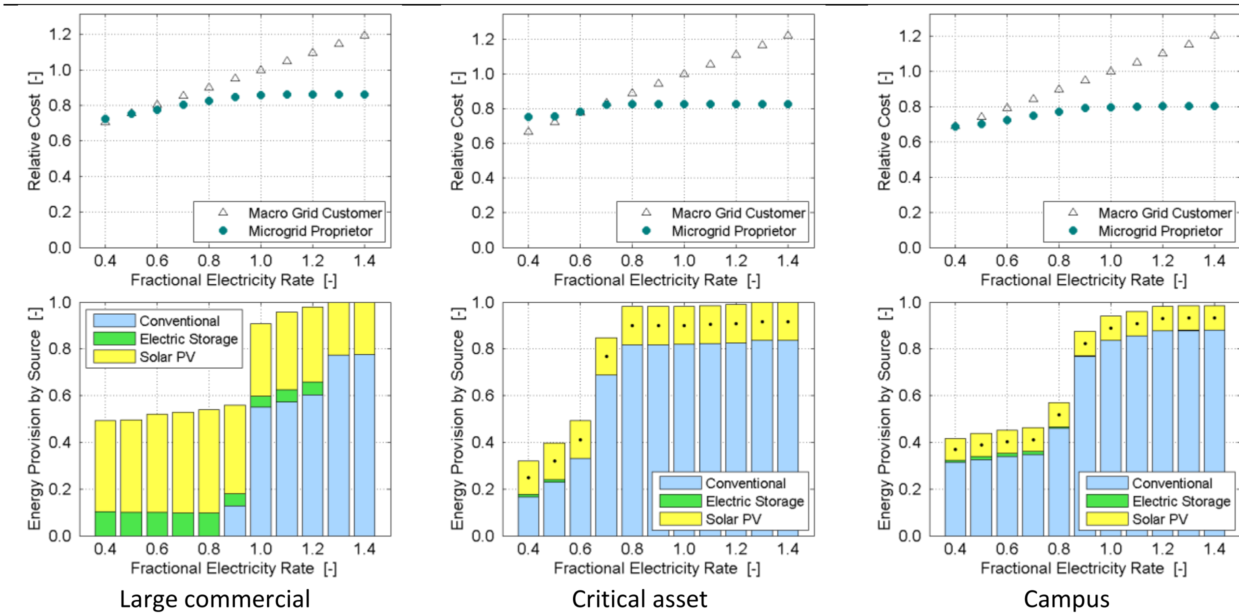


Figure 6: The total energy cost is presented for the macro grid customer and microgrid proprietor (top). Costs are normalized by the total energy cost of the macro grid customer for the nominal volumetric charge (unity). Energy provision by source is presented for the microgrid proprietor across variation in volumetric charges (bottom). Each bar is a separate model run and the remaining unfilled portion of the bar represents grid purchases. A black dot in the bar for solar PV provision denotes that solar PV installations are space-constrained.

Figure 7 presents the total energy cost to the macro grid customer and microgrid proprietor for varying demand charge as well as the breakdown of energy provision by source for the microgrid. Demand charges are varied fractionally from 0.4-1.4 in increments of 0.1, where the unity fractional value is the nominal value in the electric tariff. The demand charge is assessed monthly based on the maximum peak demand during the month. The macro grid customer's relative cost thus increases linearly with increasing demand charge. We observe that peak shaving is a key component of the business model for all microgrids over the wide range of demand charges. For charges <0.6, the total energy cost to the microgrid typically exceeds that to the macro grid customer, and adoption is uneconomical. For charges >0.6, the total energy cost increases slightly and soon plateaus. Here the microgrids purchase electricity minimally and self-generate to supply close to 100 percent of demand, thereby reducing the demand charge to zero or close to zero in each case.

For present-day demand charges (unity fractional demand charge), it is economical for each microgrid to peak shave and, further, self-supply nearly all demand. The critical asset microgrid, with its high premium for reliability, invests in conventional generators to supply critical load in the event of outages independent of the demand charge, and hence sees a business case for peaking shaving for demand charges 0.4-1.4. The large commercial and campus microgrids do not have so critical a need for reliability—they revert to grid purchases when demand charges are small. For these two microgrids, we observe a sharp transition (0.8-1.0 for the former, 0.7-0.9 for the latter) separating two modes of energy provision—grid purchases when demand charges are small and conventional generation when large. Present-day demand charges thus lie near this inflection point that separates two distinct business models—one based around investment in renewables and partial self-generation, and another around investment in convention generators and (close to) full self-generation.

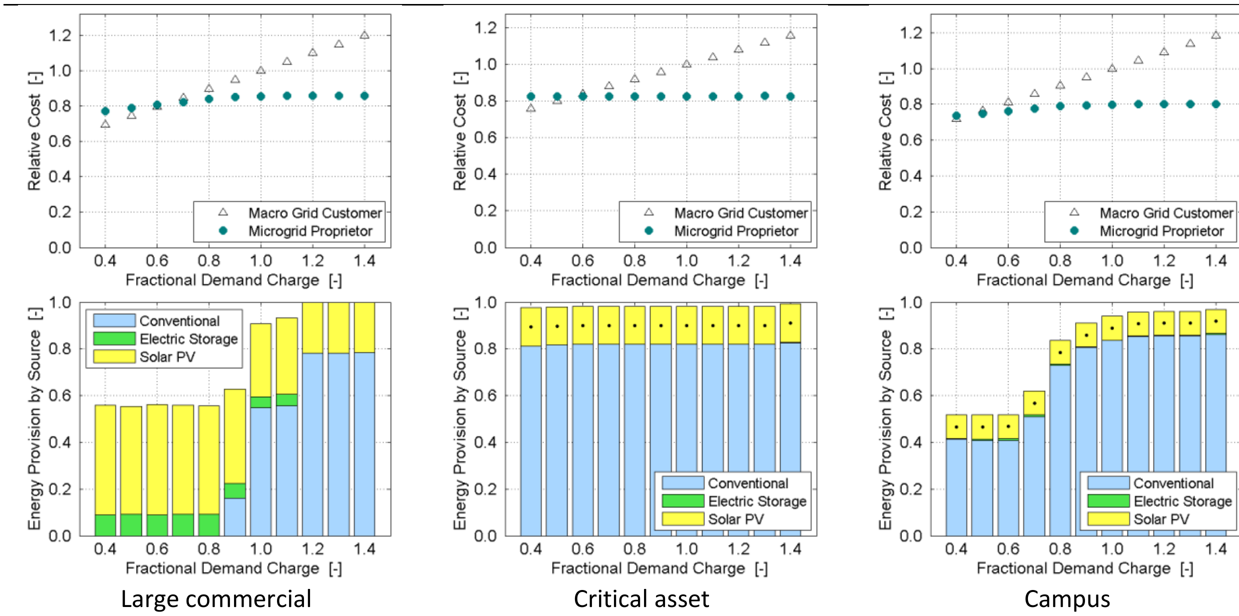


Figure 7: The total energy cost is presented for the macro grid customer and microgrid proprietor (top). Costs are normalized by the total energy cost of the macro grid customer for the nominal demand charge (unity). Energy provision by source is presented for the microgrid proprietor across variation in demand charges (bottom). Each bar is a separate model run and the remaining unfilled portion of the bar represents grid purchases. A black dot in the bar for solar PV provision denotes that solar PV installations are space-constrained.

4.3.3. Cost of carbon

Establishing a cost of carbon is one means to monetize emissions and incentivize investment in emission reduction technologies such as renewables and energy efficiency. To analyze the relationship between carbon cost and microgrid investment cases, we vary the carbon cost from 0-132 \$/MT CO_2e to capture 129 \$/MT CO2e, the 95^{th} percentile social cost of carbon for the year 2020 [114], with results shown in Figure 8[3].

We find that increasing carbon cost leads to divestment in conventional generators. The commercial microgrid supplies nearly 80 percent of load with conventional generation at a carbon cost of 0 \$/MT CO_2e and only 15 percent at 30 \$/MT CO_2e. For carbon costs >36 \$/MT CO_2e, conventional generators are not optimal; instead, solar PV and electric storage are preferred in conjunction with grid purchases.

The critical asset and campus microgrids also divest in conventional generators in response to rising carbon cost; however, they increase grid purchases rather than transition to 100 percent renewables, due to the solar PV space constraint. In fact these two microgrids maximize investment in solar PV (up to the point where space constraints are binding) to facilitate peak shaving, irrespective of the carbon tax.

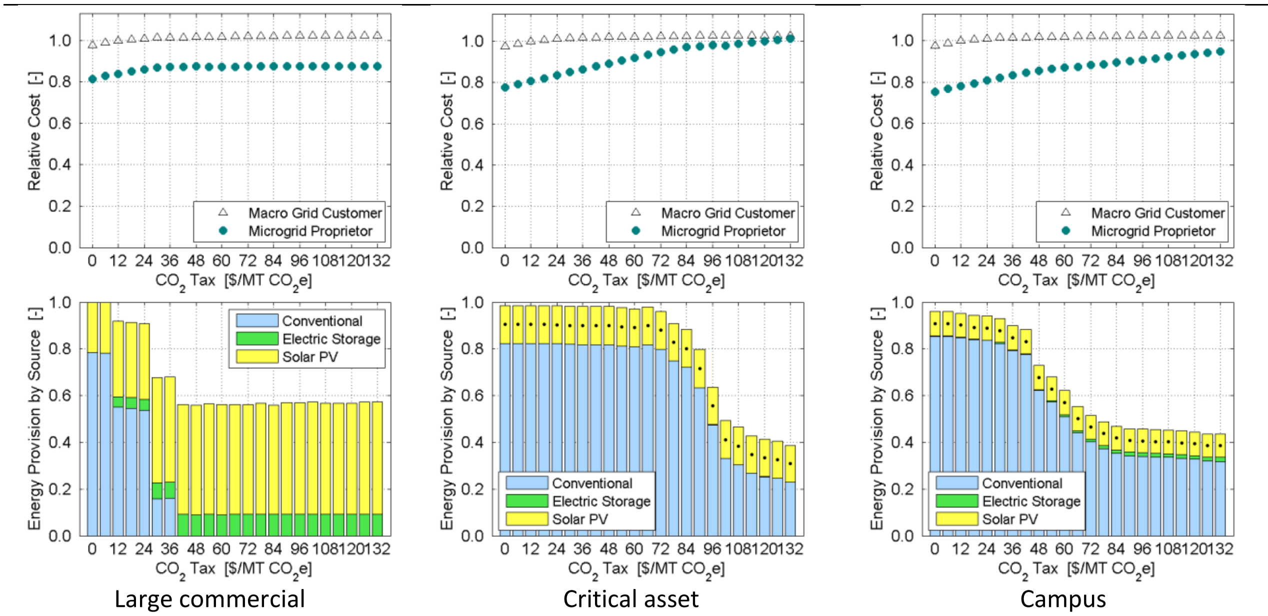


Figure 8: The total energy cost is presented for the macro grid customer and microgrid proprietor (top). Costs are normalized by the total energy cost of the macro grid customer for the nominal carbon cost (12 \$/MTCO_2e). Energy provision by source is presented for the microgrid proprietor across variation in the cost of carbon (bottom). Each bar is a separate model run and the remaining unfilled portion of the bar represents grid purchases. A black dot in the bar for solar PV provision denotes that solar PV installations are space-constrained.

[3] We increase the volumetric charge as the carbon cost increases to account for a corresponding increase in generation costs from fossil fuel power plants and subsequently the clearing price in the CAISO wholesale market and retail rates. We use AEO 2014 projections and compare the percent difference in economy-wide electricity generation costs between the “Reference case” and “Greenhouse gas \$10” scenarios. We apply the difference as a percent increase to the generation portion (taken to be 7/16 in SDG&E’s service territory) of the volumetric charge.

4.3.4. Cost of electric storage

Electric storage is widely considered a great enabler of microgrids, especially as regulators seek greater renewables penetration in the electric system. Storage costs are decreasing rapidly, and many believe low cost storage can enable widespread deployment of low-carbon microgrids. The point at which deployment becomes cost effective is an open question, however, which others have investigated [118]. To explore this important trend we reconfigure our models with varying electric storage cost—we use as a baseline a projected turnkey cost estimate (350 $/kWh) that aligns with estimates of current and projected energy storage costs over the next 5-10 years. We vary the electric storage cost 0-1150 $/kWh, the justification for which is as discussed in section 4.2 for the simple sensitivity analyses.

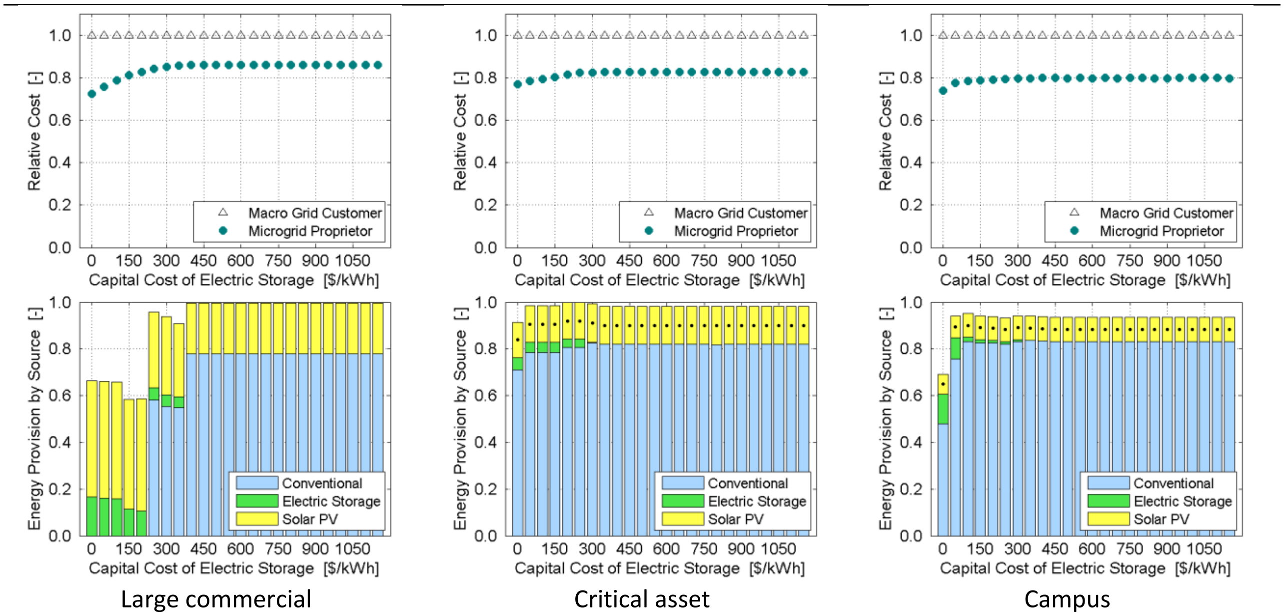


Figure 9: The total energy cost is presented for the macro grid customer and microgrid proprietor (top). Costs are normalized by the total energy cost of the macro grid customer for the nominal electric storage cost (350 $/kWh). Energy provision by source is presented for the microgrid proprietor (bottom) across variation in the cost of electric storage. Each bar is a separate model run and the remaining portion of the bar that is unfilled represents grid purchases. A black dot in the bar for solar PV provision denotes that solar PV installations are space-constrained.

The commercial microgrid adopts an increasing amount of storage as costs fall. Two transitions are salient in the set of optimal configuration. The first occurs when storage is first adopted, at 350 $/kWh, and the second occurs when the microgrid adopts a low-carbon configuration, at 200 $/kWh. With these transitions, the microgrid imports additional grid electricity and eventually supplies over 30 percent of demand with grid purchases. Even with storage costs <100 $/kWh, the microgrid need not invest further in storage—solar PV and storage plateau the demand charge and together achieve perfect energy arbitrage during on-peak periods; that is, solar PV and storage are sized sufficiently to supply the whole of the on-peak load during all on-peak periods throughout the year.

The critical asset and campus microgrids also purchase more storage as costs fall, but never adopt low-carbon configurations. Conventional generators remain the bedrock throughout. Even at 0 $/kWh, storage is used only to facilitate peak shaving, as is the case in the baseline model runs in section 4.1.

The solar PV space constraint restricts solar PV installations in all cases, thereby restricting potential transitions to a low-carbon configurations, in which storage might store significant excess daytime generation from solar PV for nighttime discharge.

5. Discussion

Microgrids can in principle confer numerous benefits to all stakeholders (the owner, distribution system, and society)—by reducing energy costs for the owner, providing grid services to the distribution system, and reducing system emissions for society. Each has value and much of the work on DERs and microgrids in political science and economics is focused on how to monetize them. In this work we evaluate microgrid business models in a conservative manner by considering only the economic benefit derived from the microgrid customer's avoided energy costs and do not consider additional revenue streams from incentives, rebates, credits, participation in ancillary service markets, utility service agreements, improvements in power quality and reliability, or emissions reductions—quantifying those benefits is a topic for future research. We also neglect important demand-side flexibilities, such as demand response and load scheduling, that improve microgrid economics.

Though from an economic standpoint these models are conservative because we disregard potential revenue streams and flexibilities, technical simplifications are present in the models—concerning solar PV and energy storage, in particular—which may decrease the total energy cost reductions achieved by the three iconic microgrids. First, solar irradiance profiles, as is typical in planning models, assume clear sky conditions. Solar PV power output captures seasonal variability (across months) but not day-to-day or intraday (that is, hourly) variability. The models have an hourly timestep and cannot capture sub-hourly variability either. This has implications for demand charge mitigation and energy storage investment—the lack of variability in these models overestimates demand charge savings and decreases the need for storage and hence the value of storage to the microgrid. This affects, most notably, the low-carbon configurations we observe in some instances for the large commercial microgrid but affects the core result—that business models are gas-based and robust—less so. The bias toward less storage caused by the lack of variability could be corrected using more granular operational models or power system analysis tools, both of which are outside the scope of this work however. The development of operational models that can be used in concert with investment and planning models is a potential topic for future research. Second, loads and solar irradiance are deterministic parameters in the models. This implies, in essence, that microgrid operators have perfect forecasts, which again overestimates demand charge savings and reduces the need for and value of electric storage.

Economic conservatism and technical simplifications aside, we find for each iconic case that microgrid adoption reduces the total energy cost relative to the macro grid customer—and hence the business case for each iconic microgrid can be made based on reducing energy costs alone. Though in some scenarios microgrid adoption is uneconomical (for example, very low electricity or demand charges, such as in Figure 6 and Figure 7), adoption is for the most part economical. We find also that business cases are robust across uncertainty in key parameters such as DER costs, tariff rates, natural gas prices, and carbon costs. While these uncertainties do not undermine the case for microgrids they do have a huge impact on the optimal microgrid configuration—which, as a practical matter, is what investors actually care about. Across all microgrids the majority of power and thermal generation comes from conventional generation technologies—notably gas. For all iconic cases and across a wide range of uncertainties, conventional generation is the foundation of DER investment because these units mitigate the demand charge by peak shaving during peak hours and also reduce the volumetric charge by displacing grid-imported electricity during all hours. Solar PV and electric storage are viable and important, and indeed optimal in most cases, but serve to supplement natural gas investments rather than facilitate low-carbon microgrids.

One implication of these findings is that while utilities stand to lose business in electric sales they could gain (albeit a less lucrative) business in selling natural gas. Another implication is that the results are robust at current gas prices, but if gas prices were to climb to >12 $/mmbtu then the case for gas-driven microgrids would be much harder to sustain, in particular when it is infeasible to transition to renewables-based configurations (as we observe for the larger two microgrids).

Microgrids generate a large number of externalities (positive and negative) on electric grid operators and more broadly on society. Those externalities define roles for policy intervention. Beyond the internal costs and benefits, microgrids have larger externalities on utilities and on society more generally—especially if built and operated at large scale. The standard logic for policy intervention begins with identifying such externalities and then correcting market failures—such as with taxes and regulation to limit negative externalities and subsidies to reward positive spillovers. Devising methods for assessing those externalities is an important topic for future research, in particular two that are likely to be important for microgrids: (i) the externalities (positive and negative) that private microgrids might impose on utilities responsible for maintaining the distribution grid to which a microgrid is interconnected, and (ii) the positive externality to society that a microgrid might have on reducing emissions of carbon dioxide, the main human cause of climate warming, through higher efficiency and greater use of renewables.

6. Conclusion

In this paper we analyzed business models for three iconic microgrids in southern California using the microgrid optimization model DER-CAM. Model parameterizations are generalized where possible so as to widen the applicability of results. The three iconic microgrids are created using DOE reference building data sets for commercial buildings and align with forecasted microgrid market growth.

In section 2 we review the sprawling literature on microgrids, focusing on software tools that have been developed to model microgrids, but including also empirical studies on microgrids as well as studies pertaining to technologies, the electric grid, and regulatory issues and opportunities. The literature is expansive but focuses mostly on technical aspects of microgrids and hence lacks systematic research into microgrid business models, a gap which this paper seeks to fill.

In section 3 we identify three classes of utility customers—large commercial buildings such as offices or box stores, critical assets such as hospitals, and campuses—based on projected growth for these microgrid markets. These customers are particularly suited to host microgrids because of their load shape, capability to integrate various DERs, and footprint within a single boundary. We term these classes *iconic cases*. We constructed data sets of end-use loads for these iconic customers which are robust so as to serve as the starting point for future microgrid studies of this nature.

We used the microgrid model DER-CAM in section 4 to simulate microgrid adoption and operation for the three iconic cases, which we discuss in section 5. We introduce the concept of a macro grid customer and microgrid customer—the former supplies demand using grid purchases; the latter, with a combination of grid purchases and on-site generation. We find for each iconic case that the optimal microgrid system reduces the total energy cost relative to the macro grid customer and that business cases are robust across key parameters.

We reiterate the notion that microgrids can benefit the microgrid owner, distribution system operator or utility, and society concurrently. Microgrids facilitate energy cost reductions, help integrate renewable energy sources, and can provide a host of services to the local distribution system. In theory, these benefits could be spread equitably among stakeholders and maximized with correct policy measures. This paper demonstrates how *owners* can benefit from microgrid adoption but gives no regard to society or the utility. Society benefits when microgrids reduce system-wide emissions; the utility, when microgrids provide grid services. Future work that demonstrates how and when these three objectives—energy cost reductions to the microgrid owner, net emissions reductions, and grid service provision—can be achieved equitably is a logical next step in the development of regulatory and business models for microgrids.

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